Unified Semantic Parsing with Weak Supervision



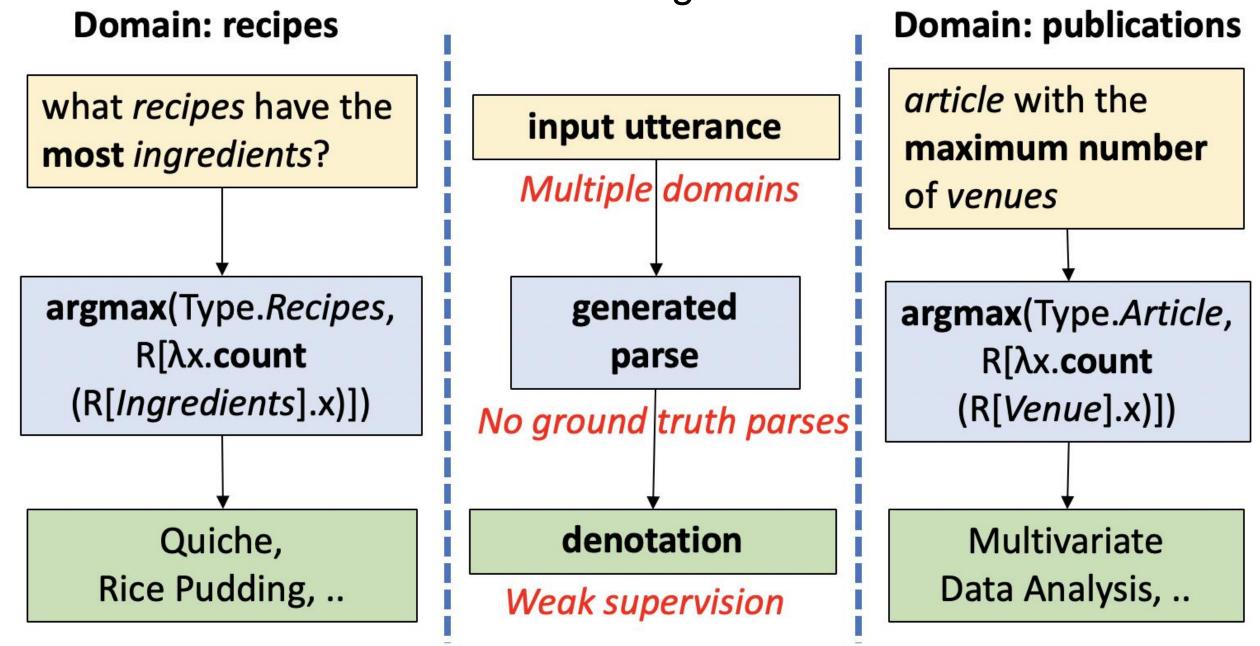
Priyanka Agrawal*, Parag Jain, Ayushi Dalmia, Abhishek Bansal, Ashish Mittal, Karthik S.

IBM Research Al

pagrawal.ml@gmail.com, {pajain34, adalmi08, abbansal, arakeshk, kartsank}@in.ibm.com

Problem

- Semantic parsing over multiple knowledge bases enables the parser to exploit structural similarities of programs across the multiple domains.
- Challenge lies in obtaining high-quality annotations of (utterance, program) pairs across various domains needed for training.



Proposed Method

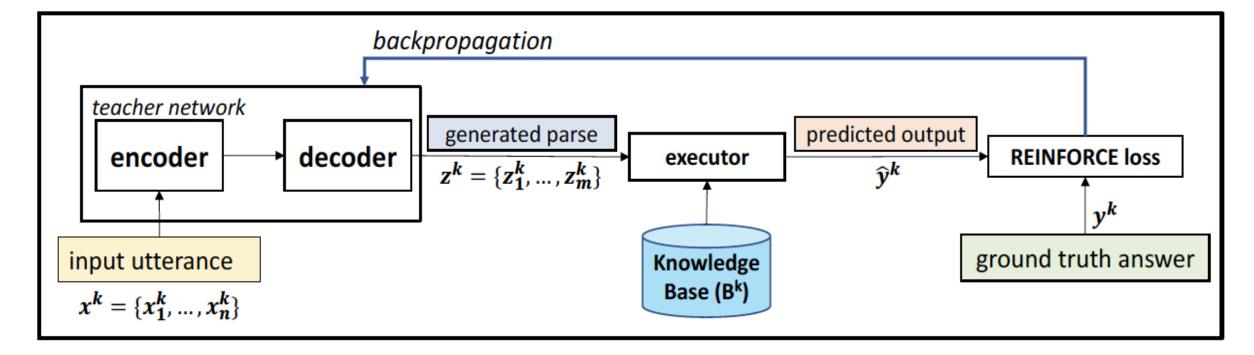
- Build a unified neural framework (DISTILLCOMBINED) to train a single semantic parser for multiple domains trained only with weak supervision i.e. using denotations in place of ground truth parse programs (Figure 1).
- Weakly supervised training is particularly arduous as the program search space grows exponentially in a multi-domain setting.
- We utilize multi-policy distillation mechanism:
 - 1. Train domain-specific semantic parsers (teachers) using weak supervision in the absence of the ground truth programs,

$$\sum_{x} \mathbb{E}_{P_{\theta}(z|x)}[R(x,z)] = \sum_{x} \sum_{z} P_{\theta}(z|x)R(x,z) \approx \sum_{x} \sum_{z \in B} P_{\theta}(z|x)[R(x,z)]$$

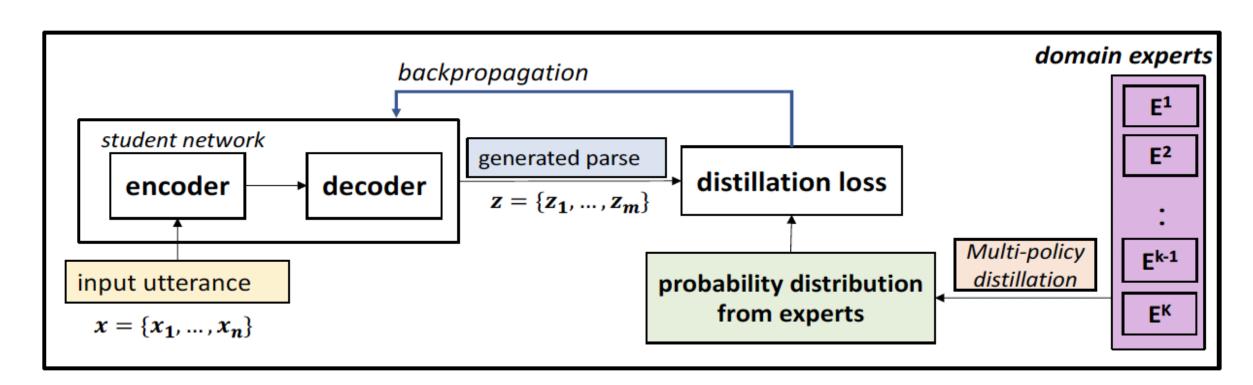
 θ : policy parameters; B: output beam containing top scoring programs; $P_{\theta}(z|x)$: likelihood of parse z

2. Train a single unified parser (student) from the domain specific policies obtained from these teachers T

$$L(\theta^{S}; \theta^{1}, ..., \theta^{K}) = -\sum_{k=1}^{K} \sum_{i=1}^{|X^{k}|} \sum_{i=1}^{|m|} \sum_{v=1}^{|\mathcal{V}|} p_{\theta}^{k}(z_{ij} = v; x_{i}^{k}, z_{i\{1:j-1\}}) \log p_{\theta}^{S}(z_{ij} = v; x^{k}, z_{i\{1:j-1\}})$$



(a) Domain specific expert policy E^k



(b) Learning a unified student S by distilling domain policies from experts E^1, \cdots, E^K

Fig 1: Proposed Architecture Diagram

Results

Baseline Models:

- 1. WEAK-INDEPENDENT: Set of weakly supervised semantic parsers, trained independently for each domain using REINFORCE algorithm.
- 2. WEAK-COMBINED: As per Herzig and Berant (2017), pool all the domains datasets into one and train a single semantic parser with weak supervision.
- 3. DISTILL-INDEPENDENT: Independent policy distillation for each domain.

Dataset: OVERNIGHT semantic parsing dataset (Wang et al., 2015) Normalized to have reduced vocab size and search space)

DOMAIN	WEAK- INDEPENDENT	WEAK- COMBINED	DISTILL- INDEPENDENT	DISTILL- COMBINED	SUPERVISED
BASKETBALL	33.8	0.5	33.8	36.3	81.0
BLOCKS	27.6	0.8	36.8	37.1	52.8
CALENDAR	25.0	0.6	12.5	17.3	72.0
Housing	33.3	2.1	42.3	49.2	66.1
PUBLICATIONS	42.2	6.2	45.9	48.4	68.3
RECIPES	45.8	2.3	61.5	66.2	80.5
RESTAURANTS	41.3	2.1	40.9	45.2	73.5
AVERAGE	35.5	2.1	39.1	42.8	70.6

Fig 2: Test denotation accuracy for each domain comparing our proposed method DISTILLCOMBINED with the three baselines. We also report the skyline SUPERVISED.

- Effect of Policy Distillation: Policy distillation of individual expert policies result in an average percentage increase of $\sim 10\%$ in accuracy.
- Performance of Unified Semantic Parsing framework: DISTILL-COMBINED approach leads to an increased performance by \sim 20% in comparison to individual domain specific teachers
- Effectiveness of Multi-Policy Distillation: Due to weak signal strength and enlarged search space from multiple domains, WEAK-COMBINED model performs poorly across domains.

Effect of Small Parallel Corpus

Adding 10% parallel data brings an improvement of about 5 points, Increasing to only 30% givens improvement of about 11 points.

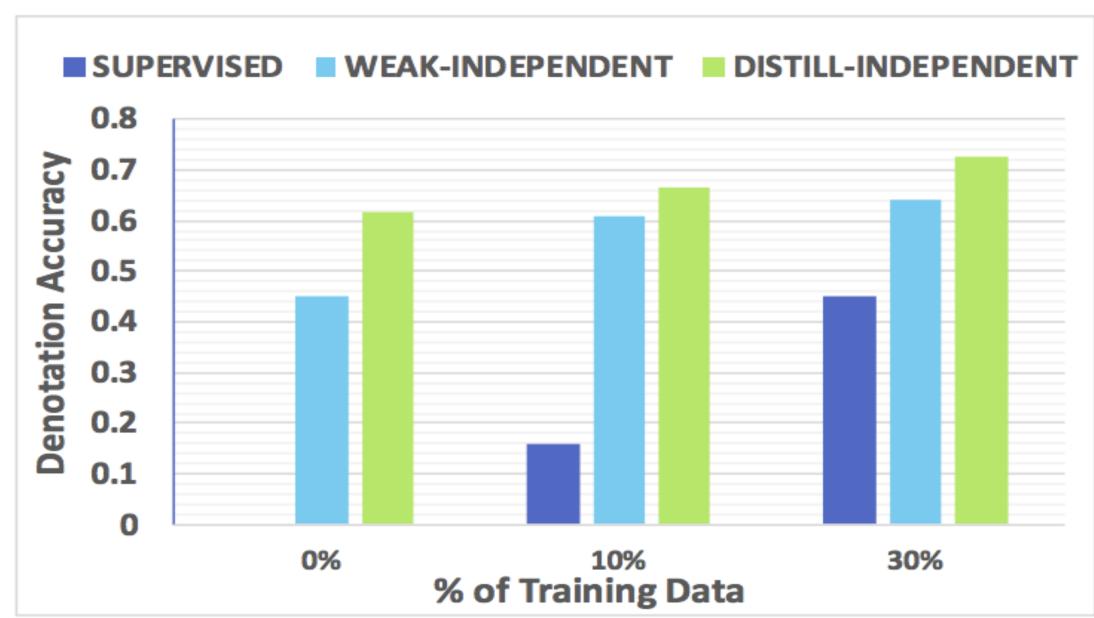


Fig: 3 Effect of the fraction of training data on different models

References

- 1. Jonathan Herzig and Jonathan Berant. 2017. Neural semantic parsing over multiple knowledge-bases. In Association for Computational Linguistics
- 2. Yushi Wang, Jonathan Berant, and Percy Liang. 2015. Building a semantic parser overnight. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics.

^{*} Priyanka has recently joined Booking.com. This work was done while she was a part of IBM Research